The 13th International Congress and Exhibition on Condition Monitoring and Diagnostic Engineering Management (COMADEM 2000), Houston, TX, USA, December 3-8, 2000.

STRUCTURAL HEALTH MONITORING AT LOS ALAMOS NATIONAL LABORATORY

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Abstract: *Structural health monitoring* (SHM) is the implementation of a damage detection strategy for aerospace, civil and mechanical engineering infrastructures. Typical damage experienced by these infrastructures might be the development of fatigue cracks, degradation of structural connections, or bearing wear in rotating machinery. Engineers at Los Alamos National Laboratory (LANL) have been actively involved in SHM research for many years. These activities have been supported by internal research funds, direct programmatic efforts, partnerships with industry, and external work for other non-defense organizations. This paper will summarize past and current SHM projects at LANL. The primary result of this work is the development of LANL's statistical pattern recognition paradigm for structural health monitoring. This paradigm will be described in detail. The paper concludes discussing the future directions for this technology that are currently being explored at LANL.

Key Words: Damage detection; statistical pattern recognition; structural health monitoring; vibrations

Introduction: The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering infrastructures is referred to as *structural health monitoring (SHM)*. Here *damage* is defined as changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the system's performance. The SHM process involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of system health. For long term SHM, the output of this process is periodically updated information regarding the ability of the structure to perform its intended function in light of the inevitable aging and degradation resulting from operational environments. After extreme events, such as earthquakes or blast loading, SHM is used for rapid condition screening and aims to provide, in near real time, reliable information regarding the integrity of the structure.

This paper is intended to provide a summary of SHM technology developed at Los Alamos National Laboratory (LANL) over the last 15 years. During this period LANL's SHM technology has evolved from *ad hoc* procedures developed on a case-by-case basis to methods based on linear modal analysis and finally arriving at general statistical pattern recognition procedures that attempt to take advantage of the nonlinearities associated with many damaging events. This learning process has culminated in the development of a statistical pattern recognition paradigm that can be used to describe all SHM problems. A summary of this paradigm will be provided. As the LANL staff's viewpoint of the SHM problem has evolved, these people have come to realize that an integrated, multi-disciplinary approach is necessary for successful SHM. Significant future developments of this technology will, in all likelihood, come by way of research efforts encompassing fields such as structural dynamics, signal processing, motion and environmental sensing hardware, computational hardware, data telemetry, smart materials, and statistical pattern recognition coupled with machine learning, as well as other fields yet to be defined. This paper concludes by describing an integrated approach to SHM encompassing many of these disciplines that is currently being undertaken at LANL.

Early studies related to structural health monitoring: Vibration-based damage detection work at LANL had its beginnings almost 15 years ago when engineers attempted to identify the onset of seismically-induced buckling in scale-model nuclear reactor containment structures from changes in their measured vibration response during shake-table testing. This work was followed by attempts to infer damage in seismically loaded scale-model reinforced concrete shear wall structures from changes in their shake-table induced vibration response (Figure 1). Also, modal testing of glove boxes, originally performed for finite element model verification, identified faulty anchorage in the glove box support structures. Through these various experimental studies it became apparent that vibration monitoring had the potential to provide a mechanism for global monitoring of structural integrity. However, damage detection was not the primary focus of these studies and no formal procedures for structural health monitoring were developed as a result of these studies.

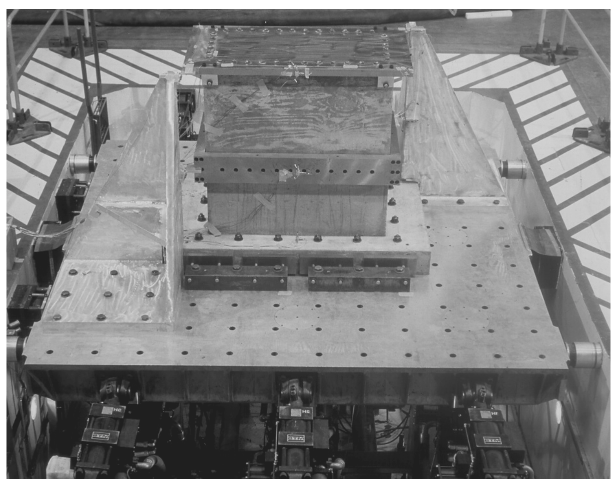

Figure 1 Scale model nuclear power plant diesel generator building mounted on a shake table.

In a parallel effort, physicists at LANL developed and patented a vibration-based damage detection system referred to as Resonant Ultrasound Spectroscopy (RUS) [1]. This system combined sine-sweep vibration testing with a homodyne detection procedure to make very precise resonant frequency measurements on small test specimens. For objects of very regular geometry, such as ball bearings, this test system was shown to provide very accurate indications of material or geometric anomalies, such as out-of-roundness of a ball bearing. Subsequent applications of RUS include the detection of salmonella poisoning in eggs from changes in their vibration characteristics, the screening of captured Gulf-War ammunition to determine if artillery shells contain conventional or chemical warheads, and detection of cracks in machined parts.

The formal study of structural health monitoring began when these physicists and engineers were asked to jointly participate in the damage detection study on the I-40 Bridge over the Rio Grande (Figure 2) [2]. These tests were performed in conjunction with engineers from Sandia National Laboratory (SNL), faculty and students from New Mexico State University, and the New Mexico State Highway and Transportation Department. The engineers from LANL performed the experimental modal analyses of the bridge in its undamaged and damaged conditions while engineers from SNL ran a hydraulic shaker that provided the input for these vibration tests. The physicists contributed to these tests by demonstrating a non-contact vibration measurement system based on a microwave interferometer designed and constructed at LANL [3].

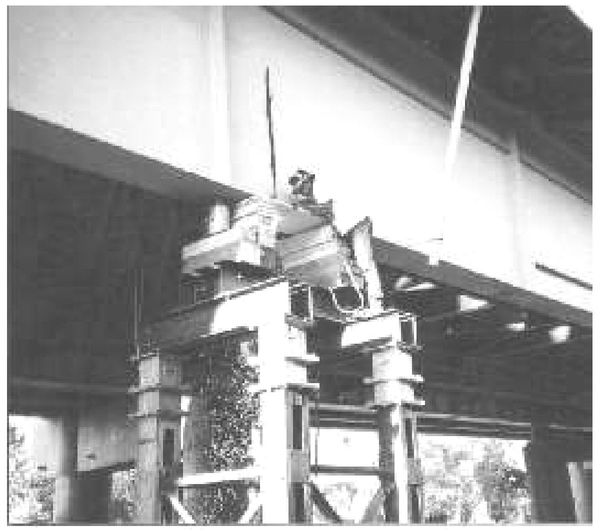

Figure 2 A technician introduces damage into a girder of the I-40 Bridge.

Participation on the I-40 Bridge tests led to internally funded research projects focused directly on vibration-based damage detection. As part of these projects the LANL staff have begun to formalize the process of structural health monitoring. The outcomes of these studies are summarized below.

Outcome of early work: The investigators at LANL can point to three primary contributions to the structural health monitoring field that have resulted from the early I-40 Bridge tests and the internally-funded investigations of vibration-base damage detection. First, a literature review of structural health monitoring studies was published, and in the authors' opinion, this review is the most comprehensive summary of the literature in this field to date [4]. Second, the computer code DIAMOND was developed. This code assembles many recently developed methods for vibration-based damage detection based on linear modal properties into one graphical user interface code [5]. The final success of these projects was the development statistical analysis procedures that can be used to quantify the variability in the measured modal properties that form the basis for many of the current vibration-based damage detection methods. Brief summaries of various projects that were conducted as part of these early formal investigations of structural health monitoring are provided below.

Results of the I-40 Bridge project: To date, field verification of damage detection algorithms applied to large civil engineering structures is scarce as few full-size structures are made available for such destructive testing. Because the I-40 bridges over the Rio Grande in Albuquerque, New Mexico were to be demolished and replaced, the investigators were able to introduce simulated cracks into the structure, perform vibration test before and after each level of damage had been introduced, and then use the test data to validate various damage identification methods. Staff from LANL and SNL performed experimental modal analyses on the bridge in its undamaged and damaged conditions. Researchers from Texas A&M University subsequently applied a damage detection algorithm to these data [6]. The same damage detection algorithm was independently applied by the LANL staff to these data and to numerical data from finite element simulations of the I-40 bridge where other damage scenarios were investigated [7]. The data required by the damage identification algorithm are mode shapes and resonant frequencies for the damaged and undamaged bridge. Results from these investigations are some of the first comparative studies of various damage identification algorithms that have been reported in the technical literature [8]. The general conclusion form this study was that linear modal properties associated with the lower frequency global modes are somewhat insensitive to local damage and subject to significant variability as a result of changing operational and environmental conditions

Results of the Alamosa Canyon Bridge Project: The Alamosa Canyon Bridge in southern New Mexico has been designated as a bridge test facility by the New Mexico State Highway and Transportation Department. Numerous modal tests were performed on this structure for the purposes of damage detection (Figure 3). With only limited abilities to introduce damage into this structure, tests focused on quantifying the statistical variations in modal properties that result from changing environmental conditions. [9, 10] It is imperative that these changes be quantified and that changes resulting from damage are shown to be either greater than or different from those resulting from the test-to-test variations.

Figure 3 Alamosa Canyon Bridge.

Statistical analysis techniques such as Monte Carlo simulation and Bootstrap analysis have played an important role in the quantification of such variability effects, as well as the incorporation of these effects into various damage identification algorithms [11].

UC-Irvine bridge column tests: The University of California, Irvine (UCI) had a contract with CALTRANS to perform static, cyclic tests to failure on seismically retrofitted, reinforced-concrete bridge columns. This project is under the direction of Prof. Gerry Pardoen at UCI. With funds obtained through LANL's University of California interaction office, LANL staff and a faculty member from the Mechanical Eng. Dept. at Rose-Hulman Institute of Technology were able to perform numerous experimental modal analyses on the columns (Figure 4). These modal tests were performed at stages during the static load cycle testing when various amounts of damage had been accumulated in the columns. With help from staff in LANL's computer science division these tests and the associated data obtained were used to develop and demonstrate a statistical pattern recognition process of vibration-based damage detection. This study represented LANL's first use of formal statistical pattern recognition algorithms in structural health monitoring studies [12].

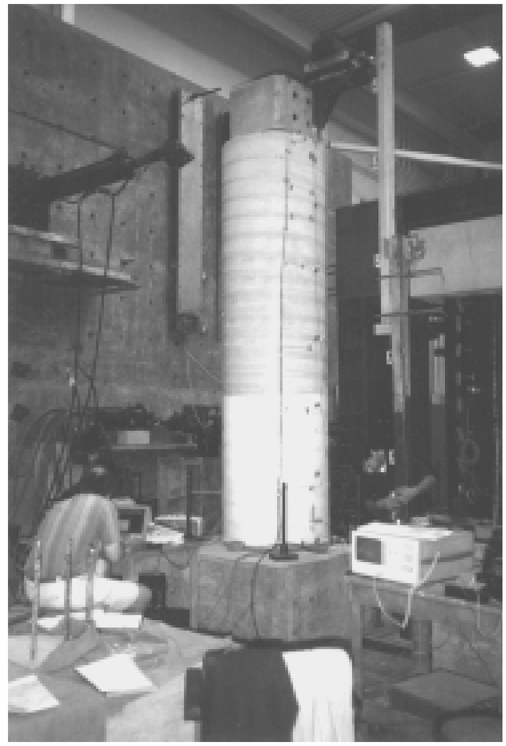

Figure 4 A modal test being performed on a bridge column at the University of California, Irvine.

A statistical pattern recognition paradigm for structural health monitoring: Through the previously summarized studies and interactions with staff in LANL's computer science division, it has been recognized that the vibration-based damage detection problem is fundamentally one of statistical pattern recognition. A statistical pattern recognition paradigm for SHM can be described in terms of a four-step process that includes 1. Operational evaluation; 2. Data acquisition and cleansing; 3. Feature extraction and data compression; and 4. Statistical modeling for feature discrimination. It is the authors' opinion that all structural health monitoring problems can be defined in terms of this statistical pattern recognition paradigm. These four steps are described below.

Operational evaluation: Operational evaluation attempts to answers four questions regarding the implementation of a structural health monitoring system:

1. What is the life safety and/or economic justification for performing the health monitoring activity.
2. How is damage defined for the system being investigated and, for multiple damage possibilities, which are of the most concern?
3. What are the conditions, both operational and environmental, under which the system to be monitored functions?
4. What are the limitations on acquiring data in the operational environment?

Operational evaluation begins to set the limitations on what will be monitored and how the monitoring will be accomplished. This evaluation starts to tailor the health monitoring process to features that are unique to the system being monitored and tries to take advantage of unique features of the postulated damage that is to be detected.

Data acquisition and cleansing: The data acquisition portion of the structural health monitoring process involves selecting the types of sensors to be used, selecting the location where the sensors should be placed, determining the number of sensors to be used, and defining the data acquisition/storage/transmittal hardware. This process is application specific. Economic considerations play a major role in these decisions. Another consideration is how often the data should be collected. In some cases it is adequate to collect data immediately before and at periodic intervals after a severe event. However, if fatigue crack growth is the failure mode of concern, it is necessary to collect data almost continuously at relatively short time intervals.

Because data can be measured under varying conditions, the ability to normalize the data becomes very important to the damage detection process. One of the most common procedures is to normalize the measured responses by the measured inputs. When environmental or operating condition variability is an issue, the need can arise to normalize the data in some temporal fashion to facilitate the comparison of data measured at similar times of an environmental or operational cycle. Sources of variability in the data acquisition process and with the system being monitored need to be identified and minimized to the extent possible. In general, all sources of variability cannot be eliminated. Therefore, it is necessary to make the appropriate measurements such that these sources can be statistically quantified.

Data cleansing is the process of selectively choosing data to accept for, or reject from, the feature selection process. The data cleansing process is usually based on knowledge gained by individuals directly involved with the data acquisition. Finally, it is noted that the data acquisition and cleansing portion of a structural health-monitoring process should not be static. Insight gained from the feature selection process and the statistical model development process provides information regarding changes that can improve the data acquisition process.

Feature extraction and data cleansing: The data features used to distinguish the damaged structures from undamaged ones receive the most attention in the technical literature. Inherent in the feature selection process is the condensation of the data. The diagnostic measurements made during a structural health monitoring activity typically produce a large amount of data. Condensation of the data is advantageous and necessary, particularly if comparisons of many data sets over the lifetime of the structure are envisioned. Also, because data may be acquired from a structure over an extended period of time and in various operational environments, robust data reduction techniques must result in the features sensitive to the structural changes of interest in the presence of environmental noise.

The best features for damage detection are typically application specific. Numerous features are often identified for a structure and assembled into a feature vector. In general, a low dimensional feature vector is desirable. It is also desirable to obtain many samples of the feature vectors. There are no restrictions on the types or combinations of data contained in the feature vector. Typically, dynamic response parameters will be combined in a feature vector with data quantifying environmental and operational conditions.

A variety of methods are employed to identify features for damage detection. Past experience with measured data from a system, particularly if damaging events have been previously observed for that system, is often the basis for feature selection. Numerical simulation of the damaged system's response to simulated inputs is another means of identifying features. The application of engineered flaws, similar to ones expected in actual operating conditions, to laboratory specimens can identify parameters that are sensitive to the expected damage. Damage accumulation testing, during which significant structural components of the system under study are subjected to a realistic accumulation of damage, can also be used to identify appropriate features. Fitting linear or nonlinear, physical-based or non-physical-based models of the structural response to measured data can also help identify damage-sensitive features.

A summary of common features used in vibration-based damage detection studies can be found in [4]. These features include, but are not limited to, those derived from basic modal properties (resonant frequencies and mode shapes), mode shape curvature changes, dynamically measured flexibility, changes in structural model parameters (elemental stiffness values) resulting from model updating procedures, non-model based time-history and spectral pattern methods, and methods based on nonlinear and/or non-stationary response introduced by the onset of damage. An example of qualitative features based on nonlinear and non-stationary response is shown in **Figure 5** where the change in the time-frequency response of a cantilever beam can be seen after a crack has been introduced into the beam.

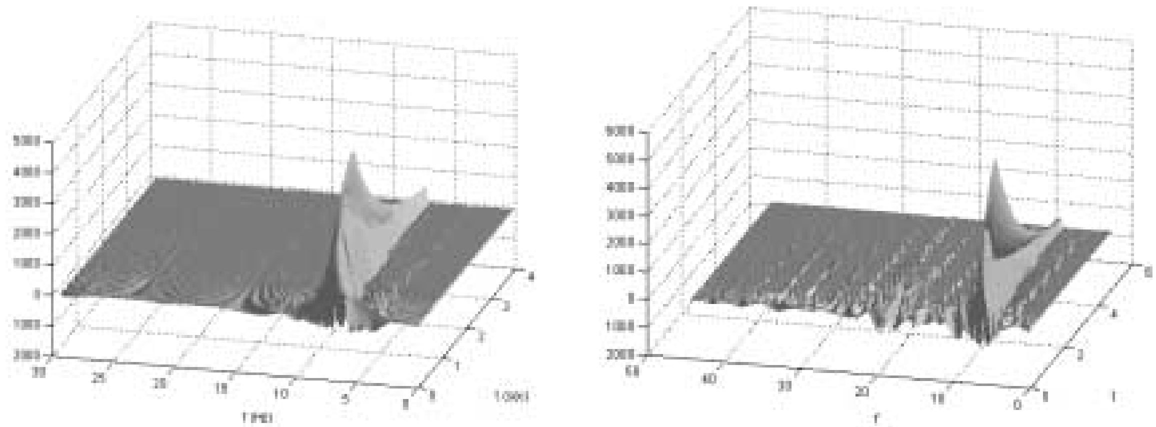

Figure 5. Time-frequency spectra of the free-vibration acceleration-time histories measured on an uncracked cantilever beam (left) and a cracked cantilever beam (right).

Statistical model development: The portion of the structural health monitoring process that has received the least attention in the technical literature is the development of statistical models to enhance the damage detection process. Almost none of the hundreds of studies summarized in [4] make use of any statistical methods to assess if the changes in the selected features used to identify damaged systems are statistically significant.

Statistical model development is concerned with the implementation of the algorithms that operate on the extracted features to quantify the damage state of the structure. The algorithms used in statistical model development usually fall into three categories. When data are available from both the undamaged and damaged structure, the statistical pattern recognition algorithms fall into the general classification referred to as *supervised learning*. *Group classification* and *regression analysis* are supervised learning algorithms. *Unsupervised learning* refers to algorithms that are applied to data not containing examples from the damaged structure. Density estimation and outlier detection are the primary statistical tools employed in an unsupervised learning mode [13].

The damage state of a system can be described in term of five different levels along the lines of those discussed in [14] to answers the following questions: 1. Is there damage in the system (existence)?; 2. Where is the damage in the system (location)?; 3. What kind of damage is present (type)?; 4. How severe is the damage (extent)?; and 5. How much useful life remains (prediction)? Answering these questions in the order presented represents increasing knowledge of the damage state. The statistical models are used to answer these questions in an unambiguous and quantifiable manner. Experimental structural dynamics techniques can be used to address the first two questions in an unsupervised learning mode. To identify the type of damage, data from structures with the specific types of damage must be available for correlation with the measured features. Analytical models are usually needed to answer the fourth and fifth questions unless examples of data are available from the system (or a similar system) when it exhibits varying damage levels.

Finally, an important part of the statistical model development process is the testing of these models on actual data to establish the sensitivity of the selected features to damage and to study the possibility of false indications of damage. False indications of damage fall into two categories: 1.) False-positive damage indication (indication of damage when none is present), and 2). False-negative damage indication (no indication of damage when damage is present). Although the second category is detrimental to the damage detection process and can have serious implications, false-positive readings also erode confidence in the damage detection process.

Fundamental challenges for structural health monitoring: The basic premise of SHM procedures that utilize vibration-based damage detection is that damage will significantly alter the stiffness, mass or energy dissipation properties of a system, which, in turn, alter the measured dynamic response of that system. Although the basis for vibration-based damage detection appears intuitive, its actual application poses many significant technical challenges. The most fundamental challenge is the fact that damage is typically a local phenomenon and may not significantly influence the lower-frequency global response of structures that is normally measured during vibration tests. Stated another way, this fundamental challenge is similar to that in many engineering fields where the ability to capture the system response on widely varying length scales, as is needed to model turbulence or to develop phenomenological models of damping, has proven difficult. Another fundamental challenge is that in many situations vibration-based damage detection must be performed in an *unsupervised learning* mode. Finally, data normalization poses as significant challenge for this technology if environmental and operational variability are to accounted for in the damage diagnosis process. These challenges are supplemented by many practical issues associated with making accurate and repeatable vibration measurements at a limited number of locations on complex structures often operating in adverse environments.

The future: integrated structural health monitoring: The goal of current research efforts at LANL is to develop a robust and cost-effective SHM system by integrating and extending technologies from various engineering and information technology disciplines. The system will be composed of both hardware and software components. Changes in dynamic response resulting from damage will be detected with sensitive, dynamic response measurements made with *active* Micro-Electro Mechanical Systems (MEMS) and fiber optic sensing technology. Here the term *active* indicates that the sensing units will be designed to provide a local mechanical excitation source tailored to the monitoring activity. Software for data interrogation will incorporate statistical pattern recognition algorithms to identify that damage is present. Damage will be located by examining the transmissibility between a local array of sensors using cross-correlation techniques. The software will be integrated into the sensing unit through a programmable micro-processing chip. The processed data output of these sensing units will be monitored at a central location using a wireless data transmission system. This integrated system, depicted in Figure 6, is being developed with the intent that it can be adapted to monitor a variety of engineering systems. These systems include aircraft, space vehicles, rotating machinery in semi-conductor manufacturing facilities, and buildings and bridges in high seismic regions. This strategy for SHM offers a potential for a significant breakthrough in this technology through an integrated sensing/data interrogation process that, to the author's knowledge, has not been attempted to date.

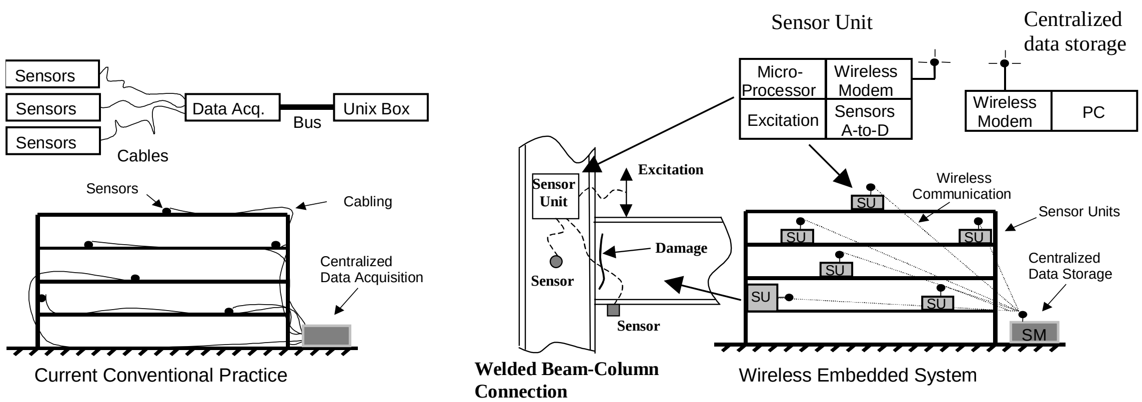

Figure 6. The current LANL research objective: Move from a conventional wired, off-the-shelf sensing system to an active wireless system developed for a specific health monitoring activity.

Acknowledgments: The authors of this summary would like to thank the following people whose work is summarized in this paper: William Baker, Philip Cornwell, Tim Darling, Thomas Duffey, Norman Hunter, Albert Migliori. The managers, support personnel, university students, and collaborators who have been involved in these studies also deserve more credit than can be offered herein. Los Alamos National Laboratory is operated by the University of California for the United States Department of Energy.

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